AI-Assisted FM Broadcasting Monitoring and Localization

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Abstract. Artificial intelligence (AI) is widely used in the fields of images, voice, games, etc., but very few is reported in the field of radio monitoring. In order to achieve automatic and intelligent FM broadcasting monitoring, an AI-assisted FM broadcasting monitoring and localization system which consists spectrum sensing node (SSN) cluster and server is presented in this paper. In the system, we monitor the radio spectrum in FM band, and use convolutional neural network (CNN) to classify the spectrum data and realize the discrimination between licensed and unlicensed broadcasting. For localization of unknown transmitter, three SSNs are deployed in the campus of Yunnan University, which is divided into 12 regions. A transmitter is located at each region to transmit broadcasting signal, while each SSN receive the spectrum data and send it to the server to construct a fingerprint database for further location of unknown transmitter. Through collecting the spectrum datasets in the experiment, both the received signal strength (RSS) and the spectrum data fingerprints-based localization strategies are implemented based on AI algorithms.

Introduction

Radio monitoring is used to monitor the situation for the use of radio, and eliminate the radio interference. Therefore, the ability to identify unlicensed radio and locate unknown transmitters is crucial to avoid harmful radio interference. Existing problems of current radio monitoring systems include the following [1-3]: Mainly consisting of large and expensive monitoring equipment, with which to build large-scale spectrum monitoring systems would be high cost and inefficient; Not information systems but communication systems, and complying with Radio Monitoring Transfer Protocol just for data transmission, in which facilities transfer monitoring data originally without processing; Little effort to dig large amounts of spectrum data acquired by monitoring equipment for all benefits, especially to utilize the time and location dimensions of the radio frequency.

Recently, some technologies have been used to upgrade incumbent spectrum monitoring systems. In the aspect of system architecture, Cooklev et al. presented a cloud-based system-of-systems for spectrum monitoring, and they described the interface to the cloud as an important enabler and proposed a solution that allows ontology descriptions to be used for both spectrum management and monitoring [4]. Baruffa et al. presented the big data architecture for spectrum monitoring in cognitive radio applications [5]. Yang et al. proposed the compressed cooperative eigenvalue spectrum sensing method just for data transmission, in which facilities transfer monitoring data originally without processing; Little effort to dig large amounts of spectrum data acquired by monitoring equipment for all benefits, especially to utilize the time and location dimensions of the radio frequency.

In the aspect of Artificial intelligence, Azmat et al. analyzed the spectrum occupancy in cognitive radio networks using different machine learning techniques, and the numerical results showed that support vector machine was the best algorithm among all the supervised and unsupervised classifiers [7]. Ali et al. demonstrated a novel method for the automatic modulation classification based on a deep learning autoencoder network, trained by a nonnegativity constraint algorithm. The results indicate that the autoencoder with nonnegativity constraint improves the sparsity and minimizes the reconstruction error in comparison with the conventional sparse autoencoder [8]. Yu et al. developed a spectrum monitoring...
prediction framework with a deep learning approach on two real-world spectrum datasets, and compared the prediction performance of the Long short-term memory neural network and conventional multilayer perceptron neural network [9]. Ding et al. provided a comprehensive survey and tutorial on the recent advances in spectrum inference, and highlighted the critical research challenges and open issues ahead [10].

This paper presents an AI-assisted FM broadcasting monitoring and localization system. Firstly, an automatic and intelligent FM broadcasting monitoring system architecture is proposed, which is a machine-machine system and realizes data acquisition, processing, storage and display. Secondly, a detection method of FM broadcasting signal based on CNN is used to distinguish all FM broadcasting signals and noise in the spectrum, and then the results are compared with licensed broadcasting database to discriminate licensed and unlicensed broadcasting. Thirdly, in order to locate the unknown transmitter, a fingerprint-based localization method is adopted, which utilizes RSS, spectrum data and the region number of the transmitter as location fingerprints. Different machine learning algorithms are adopted to locate the transmitter based on RSS fingerprints and spectrum data fingerprints.

**Architecture of the System**

As shown in Fig. 1, the system mainly consists of SSN cluster and server. The SSN cluster takes charge of unlicensed signal detection and sending monitoring data to the server. The server controls the working state of the SSN cluster and further processes, stores and presents the received data.

The hardware used in the design of the SSN includes an embedded industrial computer, a 14-bit software defined radio (SDR) receiver, a FM antenna and a GPS device. The signal analysis processing software module of the SSN was developed in the Ubuntu 18.04LTS system using the Python. The server is a 2U Rack industrial computer, installed with Windows 10 system, where the Django web development framework, the Bootstrap front-end framework, and the MySQL database are used to develop the B/S mode software system. In order to establish communication between SSNs and server in different areas of the campus, a switch and several wireless bridges with model of Mercury 505 are used to construct local area network (LAN).

![Figure 1. Architecture of the system.](image1)

The block diagram of the system is shown in Fig. 2. During daily monitoring, the SSN sweeps in the frequency range of 87MHz to 108MHz, and the spectrum data is analyzed in the AI-assisted monitoring module, which uses the CNN-based FM broadcasting signal monitoring method. The data is transmitted to the server for further processing and the processing results will be send to the cloud which is intuitively available to regulators.

When an unlicensed broadcasting is detected, the system turns to unlicensed signal monitoring mode, that is, the server switches the working frequency of all SNNs to the unlicensed broadcasting frequency $f_0$ for single frequency monitoring. The monitoring data is sent to the server and stored in MySQL database, where the fingerprint database is constructed for the localization of unknown unknown

![Figure 2. The block diagram of the system.](image2)
transmitter. In AI-assisted localization module, different pattern matching methods are used to locate the transmitter.

**Method and Experiment**

In the experiment, we designed the system according to the architecture as shown in Fig. 1. A photograph of a SSN is shown in Fig. 3. A FM transmitter with a maximum power of 25W is used to transmit FM broadcasting signals on campus of Yunnan University. We use the car power to charge the FM broadcasting transmitter, of which the antenna is placed on the roof of the car, as shown in Fig. 4. The transmitting frequency of the transmitter is set to 88MHz, and the transmitting power is 0.9W.

![Figure 3. Spectrum sensing node.](image1)

![Figure 4. Transmitting FM broadcasting signal.](image2)

**FM Broadcasting Monitoring**

The bandwidth of each FM broadcasting signal is 0.2MHz. We divide the spectrum data into FM broadcasting signal, noise and non-FM broadcasting signal, as shown in Fig. 5. Spectrum data are collected for each of the above three types. CNN is used to train the FM broadcast signal monitor model, and the trained model is exported and integrated with the system. When the spectrum data is input into the signal model, all the FM broadcasting frequencies can be obtained, which are compared with the local licensed FM broadcasting database to distinguish licensed and unlicensed broadcasting.

![Figure 5. FM broadcasting signal, noise and non-FM broadcasting signal.](image3)

![Figure 6. Location distribution of SSNs and 12 regions.](image4)

**Unknown Transmitter Localization**

We deployed three SSNs on the roof of the two buildings on campus, two of the SSNs are deployed at different locations of the same building (one is on roof, another is in the room of the 4th floor of the building). As shown in Fig. 6, we divided the campus into 12 regions and used the transmitter to
transmit 15 minutes of FM broadcasting signals in each region. After turn on the transmitter, the monitoring system runs in the unlicensed signal monitoring mode, and the server switches the working frequency of all SNNs to the 88MHz, and the monitoring data of each SSN is transmitted to the server through the LAN. The fingerprint database stored at the server is constructed with RSS, spectrum data and the location of the transmitter. In the analysis of the localization, we divide the data set into a training set and a test set according to the ratio of seven to three, and use the RSS fingerprints and the spectrum data fingerprints to locate the unknown transmitter. For RSS fingerprints based localization, the machine learning algorithms including support vector machine (SVM), multi-layer perceptron (MLP), decision trees (DTs) and random forest are implemented. For spectrum data fingerprints, CNN localization is realized.

**Results**

Fig. 7 shows a partial page view of the browser when the system is running in daily monitoring mode. The page displays the statistic results of licensed and unlicensed signals, and displays the frequency, RSS and name of each broadcasting station. The name of unlicensed radio is indicated by “unknown”. Each time when the SSN completes the monitoring, it sends data to the server and the monitoring information on the front page will be updated automatically.

As shown in Fig. 8 is a partial page view of the browser when constructing the fingerprint database. We input the region number in the input box according to the region where the transmitter is located. The data sent by the SSN to the server is displayed in real time on the browser page and stored in MySQL database along with the region number which indicates the location of the transmitter.

<table>
<thead>
<tr>
<th>Daily Monitoring</th>
<th>Unlicensed Signal Monitoring</th>
<th>Sensor Management</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Total Signals</strong></td>
<td><strong>Licensed</strong></td>
<td><strong>Unlicensed</strong></td>
</tr>
<tr>
<td>26</td>
<td>14</td>
<td>12</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Number</th>
<th>Frequency</th>
<th>RSS</th>
<th>Broadcast Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>87.6</td>
<td>-41,7473</td>
<td>Unknown</td>
</tr>
<tr>
<td>2</td>
<td>88.7</td>
<td>-42,2039</td>
<td>Yunnan Radio Economic Broadcasting</td>
</tr>
<tr>
<td>3</td>
<td>89.4</td>
<td>-42,2214</td>
<td>Unknown</td>
</tr>
<tr>
<td>4</td>
<td>89.8</td>
<td>-28,5726</td>
<td>China Central Radio Economic Broadcasting</td>
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Based on the RSS fingerprints, four machine learning algorithms include SVM, MLP, DTs and random forest are used to locate the transmitter. As shown in Table 1, we compare the accuracy of the four methods, and the results show that SVM has the highest accuracy. Its confusion matrix is shown in Fig. 9. The method of MLP has the lowest accuracy. Therefore, in our experimental environment, SVM is the best method for RSS fingerprint localization. Based on the spectrum data fingerprints, the accuracy of CNN localization is 97.46%, and the confusion matrix is shown in Fig. 10.

![Figure 7. Daily monitoring.](image1)

![Figure 8. Constructing the fingerprint database.](image2)

![Figure 9. Confusion matrix of SVM.](image3)

![Figure 10. Confusion matrix of CNN.](image4)
Table 1. Accuracy comparison of different machine learning algorithms.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>SVM</th>
<th>MLP</th>
<th>DTs</th>
<th>Random forest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>98.55%</td>
<td>97.19%</td>
<td>98.46%</td>
<td>97.92%</td>
</tr>
</tbody>
</table>

Conclusion

In this paper, an AI-assisted FM broadcasting monitoring and localization system is designed and implemented, where spectrum data can be acquired and processed automatically, and the results are intuitively available to spectrum regulators. We apply the AI-assisted technology to the spectrum monitoring of FM broadcasting and the localization of unknown transmitters. The FM broadcasting signal monitoring model based on CNN is used to extract the FM broadcasting signal in the spectrum. For localization of unknown transmitter, we compare the location effects of different algorithms based on fingerprint database. In our experimental environment, the localization accuracy of SVM method based on RSS fingerprints is the highest. At present, the system is implemented on the campus of Yunnan University. In the future, we will improve the system and deploy it in a wider region.

Acknowledgement

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References


